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SmartEle: Smart Electricity Dashboard for Detecting Consumption Patterns: A Case Study at a University Campus

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Abstract: To achieve Sustainable Development Goal 7 (SDG7), it is essential to detect the spatiotemporal patterns of electricity consumption, particularly the spatiotemporal heterogeneity of consumers. This is also crucial for rational energy planning and management. However, studies investigating heterogeneous users are lacking. Moreover, existing works focuses on mathematic models to identify and predict electricity consumption. Additionally, owing to the complex non-linear interrelationships, interactive visualizations are more effective in detecting patterns. Therefore, by combining geospatial dashboard knowledge and interactive visualization technology, a Smart Electricity dashboard (SmartEle) was designed and developed to interactively visualize big electrical data and interrelated factors. A university campus as the study area. The SmartEle system addressed three challenges. First, it permitted user group-oriented monitoring of electricity consumption patterns, which has seldom been considered in existing studies. Second, a visualization-driven data mining model was proposed, and an interactive visualization dashboard was designed to facilitate the perception of electricity usage patterns at different granularities and from different perspectives. Finally, to deal with the non-linear features of electricity consumption, the ATT-LSTM machine learning model to support multivariate collaborative predicting was proposed to improve the accuracy of short-term electricity consumption predictions. The results demonstrated that the SmartEle system is usable for electricity planning and management.

Keywords: dashboard; electricity management; visualization; heterogeneous user group

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1. Introduction

Modern energy services play a key role in improving the quality of life [1–3]. Achieving universal access to modern energy services and providing more people with sustainable modern energy services are the core of SDG7 [4]. About 840 million people worldwide still did not have access to electricity energy at the end of 2017 [5]. Electricity consumption has a clear spatiotemporal pattern owing to the consumers' space–time distribution. However, obtaining accurate assessments of the spatiotemporal patterns of electricity consumption and exploring the factors that influence electricity consumption are crucial for electricity planning and management [6–10].

The campus is a fully functional community with remarkable electricity consumption spatiotemporal patterns. From the perspective of electricity consumption, a campus contains multiple functional community areas, for example, for living (dining, accommodation), learning (classroom, library) and leisure (sports), within a small area. In a campus, buildings, as basic units of electricity energy consumption, have a latent spatiotemporal pattern in terms of electricity consumption. From the perspective of user groups, the campus has significant diversity, particularly in Chinese campuses, including teachers, researchers, students and employees' families. Moreover, campus user groups have remarkably regular activities, strong aggregation, stable groups and similar behaviors [11]. From the perspective of the factors influencing electricity consumption, residential community electricity consumption is susceptible to the combined effects of several factors, such as household structure, electricity prices, customer lifestyles and behaviors, weather and consumption levels [12–14]. However, in a campus, in addition to external factors such as weather, inherent factors such as the behavior of user groups and their mobility also determine electricity consumption [10,15]. Therefore, there is a more stable and latent spatiotemporal pattern in a campus.

Using a data-driven approach to model user electricity consumption behavior is an effective tool for identifying user consumption patterns and analyzing the factors that affect electricity consumption [16–19].

However, some challenges are still encountered in analyzing the electricity consumption of a campus. First, the existing works focus on the data itself but ignore the user groups' heterogeneity. The users in a campus include various groups that represent different electricity consumption patterns. Only a few works have measured the influence of user groups' heterogeneity. Second, it is not easy to visualize complex non-linear electricity consumption data. In particular, accounting for the spatiotemporal patterns within the electricity consumption data is a harder task within electricity planning and management [20]. Third, an effective mathematic model to predict short-term electricity consumption patterns is lacking, due to the complex spatiotemporal relationships. The machine learning paradigm provides a chance to improve the prediction capability.

To address these issues, a visualization-driven data mining model design was based on a specific data indexing mechanism to effectively sense the integrated electricity consumption within a campus. A set of coupled visualizations that allow one to explore the data from multiple perspectives and at multiple levels is proposed in order to enable the observation and comparison of spatiotemporal information on electricity consumption. With these techniques, a dashboard system, called SmartEle, was designed and implemented to provide insight into campus electricity consumption patterns. The major contributions of this study are as follows.

(1) Group-oriented user electricity usage profiling: because of the heterogeneity of a campus, the electricity consumption patterns of different functional communities and buildings were compared and analyzed to detect correlations and differences in the electricity consumption of different user groups.

(2) An interactive framework: a visualization-driven data mining model and a set of coupled visualizations are proposed to support the sensing of campus electricity consumption from multiple perspectives and at multiple granularities.

(3) A multivariate collaborative predicting model is proposed to predict short-term electricity demand with improved prediction accuracy, providing a scientific basis for rational power planning.

2. Related Work

In recent years, urban electricity data have received extensive attention from many scholars within China and overseas, mainly in the fields of electricity consumption behavior analysis, grid working condition monitoring, electricity consumption monitoring and prediction [21,22].

2.1. Electricity Consumption Behavior Analysis

Electricity consumption behavior analysis refers to the use of data mining technology to analyze users' behavioral habits from massive, heterogeneous and multidimensional electricity data to identify user groups with distinct behavioral characteristics and to analyze the electricity consumption patterns of different groups. The most widely used method in existing electricity consumption behavior research is cluster analysis, and some scholars have also implemented user portraits to analyze electricity consumption behavior patterns.

It is common to use a clustering algorithm to analyze users' electricity consumption behavior. For example, Zhang [23] used the K-means clustering algorithm to analyze users' electricity consumption behavior for event sequence features such as peak hour consumption rate, load rate and the valley coefficient. The neighborhood residential users were divided into five categories. Xu et al. improved the K-means algorithm to extract feature curves from the classification of customer load curves, analyzed the characteristics of users' electricity consumption behavior, and realized the classification and identification of different user types [24]. They extracted the characteristic parameters of electricity consumption levels and patterns based on the probability distribution model of clustering, and plotted the residential electricity consumption curves of 16 clusters [25]. Another study [26] clustered monthly electricity consumption data and monthly average temperature separately to study the effect of weather on electricity consumption. Association rules for atmospheric temperature and user electricity consumption, neighborhood geographic features and electricity consumption were generated separately to explore users' electricity usage patterns in specific spatial features. However, data analysis and optimal selection of the electricity consumption behavior feature set were neglected in that study. Therefore, some scholars have proposed an optimization strategy for users' electricity consumption behavior features for better optimization and selection of the feature set, based on which the optimized electricity consumption behavior analysis can be realized [27,28].

The user portrait algorithm helps us to quickly understand the users' electricity consumption characteristics, so some scholars have applied it in the electricity power field. One study [29] analyzed users' electricity consumption by establishing a library of user electricity consumption behavior tags and identifying the users' electricity consumption patterns, ultimately realizing electricity consumption behavior pattern portraits for different types of users. Zhang first used a double clustering algorithm to analyze users' electricity consumption behavior, then used K-means clustering to analyze the results and finally obtained a park-level portrait of users' electricity consumption [30].

The major limitations of these electricity consumption behavior studies are as follows: (1) Most studies have analyzed users' electricity consumption behavior in terms of individual differences, while ignoring user group characteristics and inter-groups differences; and (2) the functional structure in the study area was relatively homogeneous, although with a complex functional structure. Precise analysis of the differences in electricity consumption in different functional zones was the focus of the study.

2.2. Electricity Consumption Data Visualization

Electricity data are the basis for power system operation and management. Screening and visualizing useful information from massive electricity data is essential to reveal the inner laws and future trends of electricity data, and thus improve the operability of data and the efficiency of power workers [31,32]. Visualization technology provides support for real-time monitoring of a power system's operating conditions [19]. Depending on the type of electricity data and analysis needed, choosing the right visualization method can help visually express the characteristics of the data [21,33]. One study [34] based on two data analysis methods, query and clustering, made a visual analysis of users' electricity consumption behavior. Zhao used topology diagrams for a visual analysis of power tide data [35]. Gegner et al. used animated loops and scaled text-sized line graphs to display electricity data across a wide area network, avoiding the disadvantage that a static visualization can only display data in a single time period, and visualized the geographical information of the data [20].

Most of these studies visualized single series electricity data in some way or visualized the results of analyzing multiple datasets, but there is a lack of a simple and intuitive method of visualization for comparative analysis among multiple data series. The goal of overlapping comparison visualization technology is to overlap multiple data by different visual means in a display space, making data analysis and comparison more concise and efficient, and realizing the dynamic display among data [36]. Li [37] used color coding to visualize power lines and displayed electricity data by overlaying sector maps and hotspot areas on the lines, so that the operation status of the power system and the distribution of power customers were effectively displayed. Lu [38] used color coding and overlay visualization to show the distribution of power states and the hierarchy of the power supply system, helping power workers understand the city's electrical equipment and communities' power supply at different scales. However, these studies still did not achieve a dynamic visualization of the associations of electricity data containing multiple characteristics with complex spatiotemporal relationships. For example, multiple data features could be integrated into one graphical symbol to achieve intuitive comparison and analysis of the data, as well as interactive adjustment of the parameters after the data features have been updated.

2.3. Short-Term Electricity Demand Prediction

Electricity supply is closely related to people's life and productivity. In order to rationalize the production, transmission and distribution of electricity, and to ensure the safe and smooth operation of a power system, it is necessary to predict the demand for electricity in the long term (one or several years), the medium term (weeks to a year) and the short term (hours to days) [39–42]. Among these, short-term power prediction is crucial for power management authorities to develop production scheduling plans and electricity consumption plans [43,44].

Most of the methods used in studies on short-term electricity consumption prediction have been based on time series and using machine learning. Time series predictive analysis uses the characteristics of the time of an event in the past period to predict the characteristics of that event in the future period. These models are simple and have objective prediction efficiency, but they do not predict well for series with strong non-linearity [42]. Although the prediction accuracy can be improved to a certain extent by using machine learning, with an exponential increase in the amount of electricity data, it has the disadvantages of a decrease in the ability to express effective information in the data, and slow prediction efficiency [45].

To improve the accuracy of electricity demand predictions, a combined prediction model has been proposed. For example, one study in the literature [46] integrated exponential smoothing (ETS) and advanced long- and short-term memory (LSTM) to predict monthly electricity demand for 35 European countries. Deng's EGM prediction method, which consists of EEMD, GRU and MLR, effectively improved the accuracy of short-term electricity demand predictions [47]. Yang proposed the least squares support vector machine (LSSVM) short-term electricity consumption prediction model based on VMD and SSA optimization, improving the accuracy of electricity demand predictions [42].

These electricity demand prediction studies did not consider the semantic information of the spatiotemporal characteristics of the users' location. For example, there is a big difference between electricity consumption during special periods (major events, important holidays, etc.) and daily electricity consumption. A hybrid model with a multi-objective optimizer and the support vector machine was proposed to improve the accuracy and stability of electricity demand predictions during the epidemic [48]. The spatial environmental semantic information (type of dwelling, vegetation environment and distance to roads, etc.) [26] and the functional community semantic information (residential, industrial and recreational, etc.) in geographic features have a great influence on users' electricity consumption.

3. Study Area and Task Analysis

3.1. Study Area and Data

In this study, a university located in Beijing was selected as the research area. As independent communities within a city, a campus contains multiple functional regions. The research area was divided into the teaching community, the research community, the dormitory community, the recreation community, the logistics community and the master and doctoral apartment community (the community where the teachers live) according to the heterogeneous characteristics of the functions in the campus. The study area is shown in Figure 1.

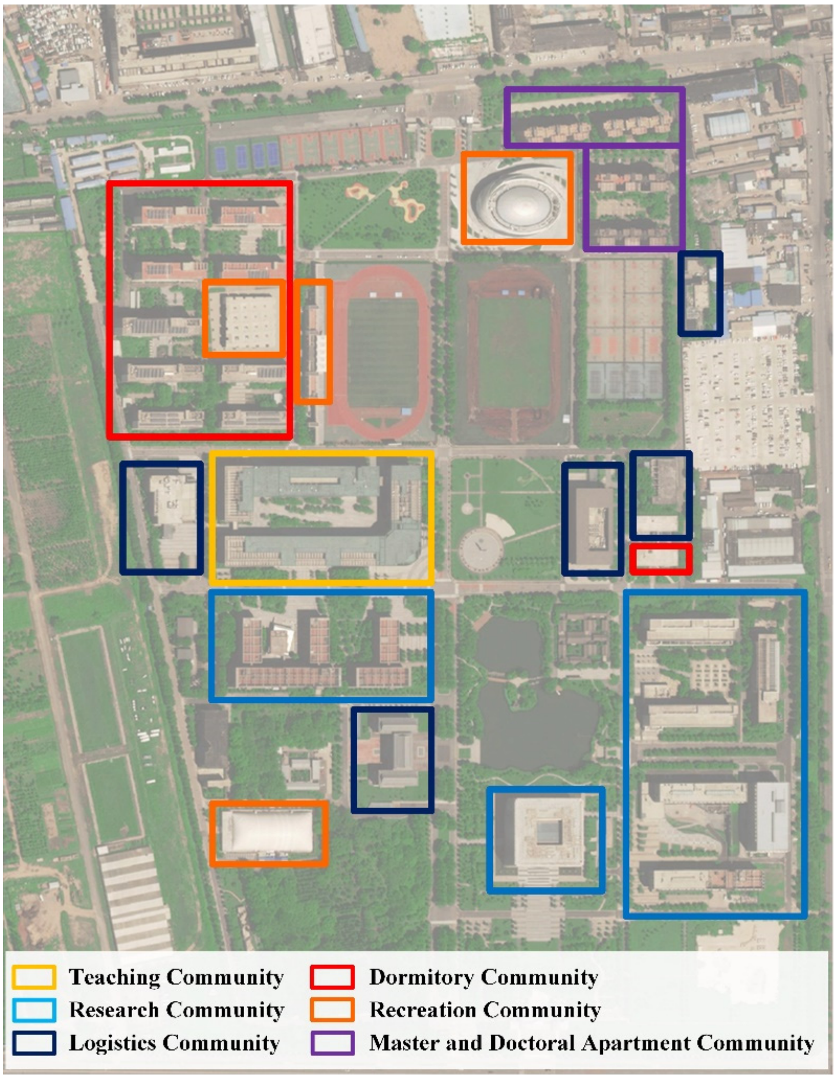


Figure 1. The university in Beijing taken as the study area.

The main data sources for this study were electricity consumption data, study area vector shape data and weather data. The electricity consumption data were the actual daily electricity consumption of buildings in the study area for 24 months during 2018–2019. The electricity consumption data used in this study are real data, provided by the fifth author and collected by the school department. The specific data were as follows: building ID, building name, electricity consumption and time. The study area's vector shape data included spatial location information and attribute data. The attribute data included the building's name, the functional community category and the electricity consumption. In addition, we used crawler technology to obtain weather data for different time intervals within the study area, including maximum and minimum temperatures.

In order to analyze the data efficiently, various data were preprocessed, stored in the database and query indices were created. The electricity consumption data were then spatialized, i.e., associated with a geographic spatial location.

3.2. Task Analysis

In order to thoroughly understand the challenges of electricity planning, interviews were conducted with experts and department heads. After these discussions, a list of analysis tasks was compiled.

T1. Community-based electricity usage analysis: What are the electricity consumption patterns of different functional communities? What are their differences? An in-depth understanding of the electricity demand in different functional regions was deemed to be conducive to the reasonable distribution of electric energy to different user groups.

T2. Time-series-based electricity usage analysis: How does electricity consumption evolve over time? What is the trend of electricity consumption for the future? By analyzing the changes in electricity consumption in different time periods, the electricity consumption patterns of different user groups can be found, which would help to realize electricity consumption predictions.

T3. Abnormal monitoring: Are there any abnormalities in electricity consumption? During the operation of the power system, abnormal power usage or signal interruption, equipment failure and other unexpected events may be encountered, resulting in abnormal electricity data. Monitoring and analyzing these abnormal values helps power workers understand abnormal power usage and the operation status of power equipment.

T4. Electricity consumption factors: What factors affect electricity consumption? The correlation between electricity consumption and each influencing factor was explored, taking factors such as seasons, weather, working days, holidays and major events into account.

T5. Integrated visualization of electricity consumption data: How can a full range of information be displayed efficiently to users? This information would help users to observe and compare important features of the electricity data. Therefore, knowing how to integrate multiple data features within one graphical symbol is the key to comprehensive visualization of the information.

T6. Interactive visualization: How can users be given the flexibility to select functional regions of interest? Does the system support the selection of time periods of interest in an interactive manner? A multi-view linkage and interactive electricity data visualization system is necessary to allow free exploration of the data and for mining more power information.

In summary, the goal of this study was to design a multi-view linked collaborative interactive visualization system that enabled electricity departments to effectively tap into the campus' electricity status, while supporting a spatiotemporal analysis of electricity consumption data and sensing the campus' electricity consumption situation and users' electricity consumption behavior. In addition, the system should provide predictions of electricity demand for future periods, which is an important step in ensuring power supply. In order to be easily understood and observed, the system should be as simple and intuitive as possible.

4. Methods

Taking the heterogeneous nature of the campus into account, a visual analysis framework was proposed to synthesize perceptions of the electricity consumption status from multiple levels and perspectives. The framework was designed in 4 parts, as shown in Figure 2. To effectively compare and analyze the differences in electricity consumption among groups, user behavior was correlated with electricity consumption in different functional communities. Similar time series were extracted for group electricity consumption patterns for building collaborative predictions. Finally, the model results were integrated in a geospatial dashboard that is advanced in terms of being a multi-scale, dynamic and interactive visualization, which adopted a pattern of tight coupling [19], thus providing an effective tool for users to freely explore the data.

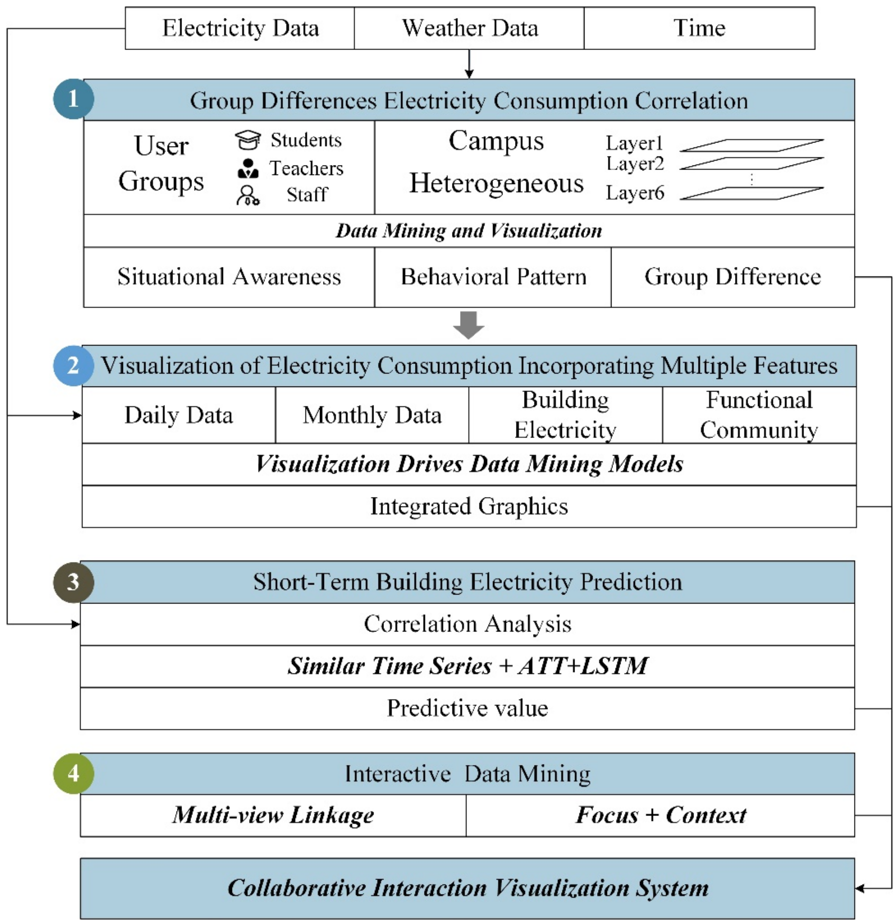


Figure 2. A visual analytics framework for integrated visualization of electricity consumption data.

4.1. Electricity Consumption Correlation Analysis for User Groups

The heterogeneity of user groups creates different demands for electricity. Therefore, measuring associations between user groups and electricity consumption is important. Group differences in electricity consumption were analyzed through qualitative and quantitative perspectives.

4.1.1. Qualitative Analysis

Two methods of mapping colors to electricity consumption using hypsometric tinting visualization were adopted: map-based heat and calendar-based heat. Map-based dynamic heat map visualization supports visual insight into the distribution relationship of groups' electricity use in space. In the map view, two functional layers are added to the ArcGIS online base map and a vector layer. The functional layer contains a heat layer and a marker layer. The heat layer is the result of color mapping of the buildings' electricity consumption level. The heat map changes dynamically according to the defined data filter. The data filter is described in Section 4.4. When the user zooms and clicks on the target building, the view will shift focus from the whole campus to the building of interest, and for the location selected by the user, an information alert box will pop up to show the location information and detailed electricity consumption information. The calendar-based heat map introduces bivariate variables, i.e., a time variable and electricity consumption. By designing a color mapping table, groups of blocks arranged in a calendar format are rendered on the basis of daily electricity consumption, with one color block representing one day's electricity consumption. This color change plays a visual accentuation role and allows the calendar heat map to clearly reflect the distribution of electricity consumption over time.

4.1.2. Quantitative Analysis

The differences in electricity consumption by different groups were perceived from two perspectives: time-series-based electricity consumption evolution patterns and community electricity consumption comparisons. Based on a time series analysis, monthly electricity consumption line graphs can be drawn for specific functional communities. Each line is automatically labeled with the maximum and minimum electricity consumption in the form of bubbles, and a dashed line indicates the average value of electricity consumption. This visualization makes it easy for power workers to keep track of the peak and trough periods of electricity consumption. Comparisons of community electricity consumption can be achieved by designing a nested ring graph that adapts to dynamic changes in the data to automatically calculate the percentage of each segment. In this case, the inner pie chart represented the first level of regional electricity consumption, i.e., the six functional communities. The outer ring represented secondary regional electricity consumption, i.e., the individual buildings in each functional community. Correlations and differences in electricity use between and within groups can be observed simultaneously.

4.2. Visualization of Electricity Consumption Data Incorporating Multiple Features

Power workers need to mine electricity consumption data from multiple levels and perspectives, which produces a huge dataset with multiple dimensional attributes. This requires a comprehensive information display tool that can intuitively perceive the status of campus electricity consumption, which would help workers to quickly understand the overall situation of campus electricity consumption and visually compare the differences among different datasets. However, if multiple dimensional datasets are overlapped and displayed in the same display space at the same time, this may cause visual complexity and create a cognitive burden for users, which is one of the challenges described earlier. Therefore, it was necessary to design a simple and effective visual metaphor to represent the integrated information.

Inspired by overlapping visualization techniques, a novel visual metaphor was designed to represent important features of the electricity consumption data. After discussions with power experts, key information for visual coding was identified, i.e., daily electricity consumption, monthly electricity consumption and individual buildings' electricity consumption data for specific functional communities. A visualization-driven data mining model (Algorithm 1) was used to integrate multiple important data features and obtain user electricity portraits for campus groups.

Algorithm 1 Visualization-driven data mining model.

Input: Multiple data features.
Output: Graphical symbols which integrate multiple data features.

```
Transformation of data
    Convert the input raw data into a standard Echarts-accepted data format
Creation of the generator
Generate the Option function
    Define the graphing method and the properties of the Option function
    Define polar axes according to the form in which the data need to be presented
    Define the graphic presentation and various attributes such as the position and style
    in the options
    Input the completed processing data into the options
Create a graphic index
    Add separate indexes for multiple graphics
Graphical overlay
    Superimpose multiple graphics according to the designed graphics index
Input the Option functions into the generator for drawing the graph
```

Considering the obvious advantages of the ring diagram for overlaying multiple layers of information flexibly, and those of the line diagram for representing temporal characteristics, a ring chart framework was used with a nested folded area chart, a bar chart, a pie chart and a round chart set into one graphical symbol. The specific graphical structure is shown in Figure 3 below.

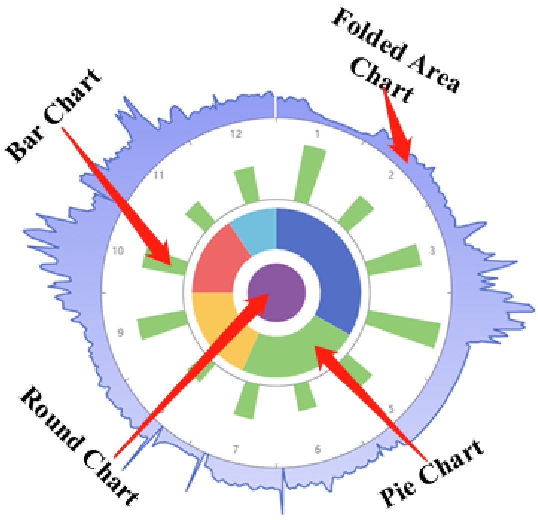


Figure 3. Graphic design structure.

Among the different charts, the folded area chart shows the daily electricity consumption of specific user groups (functional communities). The twelve bars, in a clockwise direction, represent the monthly electricity consumption of the user groups from January to December. The pie chart presents the electricity consumption of each individual building. The color of the inner circle indicates the specific user group.

4.3. Collaborative Prediction Based on Similarities in Time Variation

Electricity demand prediction is a type of time series prediction problem. Usually, historical electricity consumption is used to predict future electricity consumption for one or more days. Accurate electricity demand prediction provides a scientific basis for electricity consumption planning and the rational allocation of resources. However, the single sequence predictions in existing studies often have large errors for data that are not very cyclical and up to date, resulting in poor prediction results. An analysis of the campus electricity consumption data revealed the obvious non-smooth and non-linear characteristics of individual buildings. Therefore, the Attention-LSTM (ATT-LSTM) prediction model that considers the synergy of similar time series was proposed to predict short-term electricity consumption within the different buildings. The model's structure is shown in Figure 4.

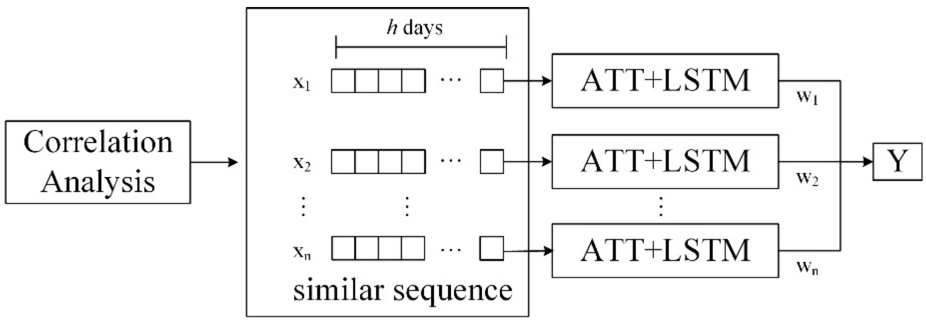


Figure 4. The ATT-LSTM prediction model that considers the synergy of similar time series.

By analyzing the correlation of a set of time series, a set of time series with some similarity was filtered and inputted into the ATT-LSTM. In this process, the attention mechanism assigns the appropriate attention to the elements according to the importance of each element learned in the sequence. The LSTM captures the long-term dependence of the time series. The predicted values of each sequence are trained with weights and then outputted. This method makes full use of historical electricity data and considers the synergistic effect of similar electricity consumption characteristics, thus improving the accuracy of short-term electricity demand predictions.

4.4. Interactive Electricity Consumption Data Mining Analysis

An effective power system needs to provide users with dynamic interactive tools. To address this need, a data filter was designed to extract the information of interest. The focus context technique was based on a data filter for analyzing the factors related to electricity usage. This not only reinforces the information of interest to the user, but also considers the connection between the focus and the surrounding area. Finally, the data between views are linked using the multi-view linking technique.

The data filter is embedded with functions that extract valid information for display based on the parameters entered by the user, enabling users to explore the data flexibly according to their interests and effectively solve T6. In the data filter, the selected target area and the custom time period are displayed from top to bottom, where the area selection is in terms of buildings and the time is in terms of months, so users can filter the areas and time period of interest.

Electricity consumption is influenced by several factors that, together with the electricity consumption data, generate a dataset with multiple dimensions. Parallel coordinate systems are very useful for expressing the correlations among multi-dimensional data. However, it is difficult to find valuable information when the dataset is too large. Therefore, the focus context technique was utilized. That is, the focus object of interest (data of interest) and the contextual environment (other data) are displayed in one view, and the data objects in the view are displayed by the established interest degree function, while the data objects in the context of the surrounding environment are weakened, realizing the effective display of the data of interest according to the user's selected interest. The principle of the focus context technique is shown in Figure 5. The method of binning was to set a local mapping function. The inputs of temporal and spatial parameters were used as conditions to judge the focus range, and the data belonging to the focus area were filtered out for mapping accordingly, while the rest of the data remained unchanged.

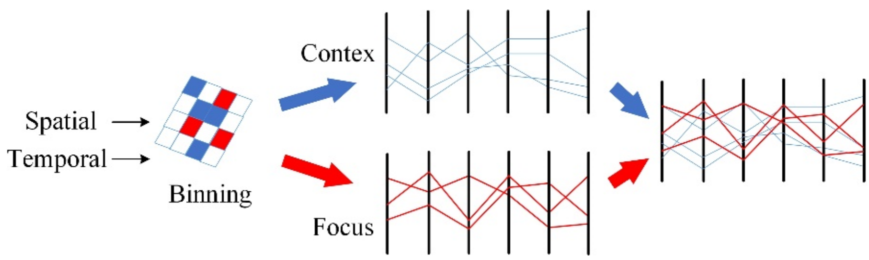


Figure 5. Parallel coordinate systems using the focus context.

A listener was designed to listen to the visual objects in multiple views and realize the dynamic associations of multiple views during an interaction by the user. This dynamically links to objects in other views when the user interacts with visual objects in any of the views. The multi-view linkage technology used broke through the limitations of difficult data connections between views and achieved a high degree of user–system interaction.

5. Case Studies

5.1. System Architecture

The innovative dashboard technology, namely the SmartEle system, was designed for multi-view interactive collaborative visualization. The system architecture is shown in Figure 6.

The SmartEle system helps users sense the electricity consumption on campus. The user initially needs to select the target area and time period, and then provide dynamic links for multiple views. When the solution areas and temporal interval have been determined, two analysis views are provided to present the electricity consumption data, i.e., location-based and time-series-based. The location-based analysis view consists of two components. On the one hand, it shows spatial differences in electricity use in the form of maps. On the other hand, it presents a comparison of electricity consumption differences by location at different levels in the form of nested pie charts. The time-series-based analysis view consists of three components. The line chart is used to grasp the electricity consumption situation at a macro-level. The calendar heat map shows fine-grained electricity consumption. The electricity prediction chart provides electricity demand for future periods. To grasp fluctuations and anomalies in the electricity consumption data, it provides a stable way of displaying the electricity consumption data's distribution that is not affected by abnormal values. Additionally, users can view the correlation between electricity consumption and different factors through the electricity consumption factors view. To further explore the differences in group electricity consumption, users can switch to the integrated information view, which integrates multiple data features in a single graph.

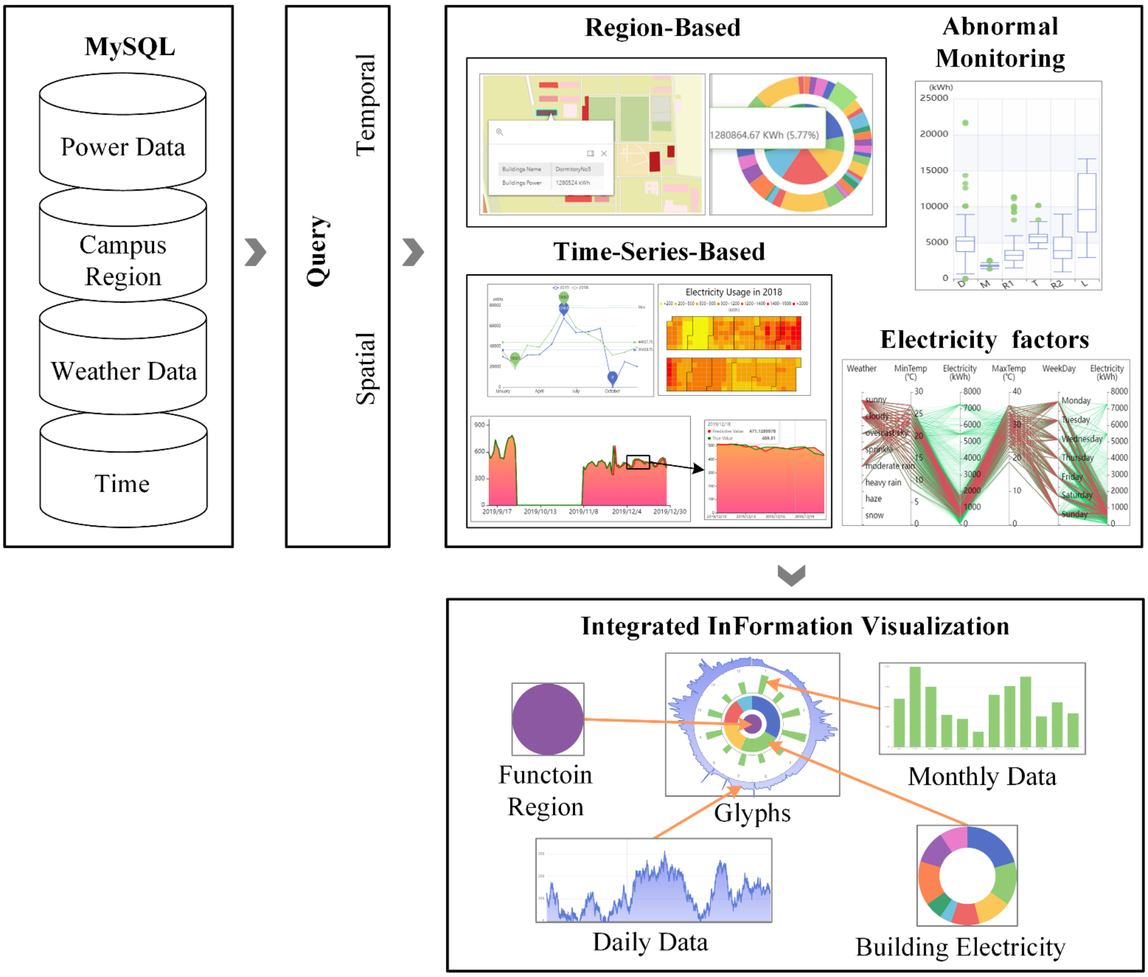


Figure 6. System architecture.

The SmartEle system uses the B/S architecture, and the database uses MySQL. The database is managed using Navicat. Backend development is based on the Express framework in the Node.js environment. The front end is based on the Vue framework using ArcGIS for JavaScript API to visualize the spatial information. The programming was carried out with the help of Vscode and pycharm software. Figure 7 shows the implementation of the SmartEle system.

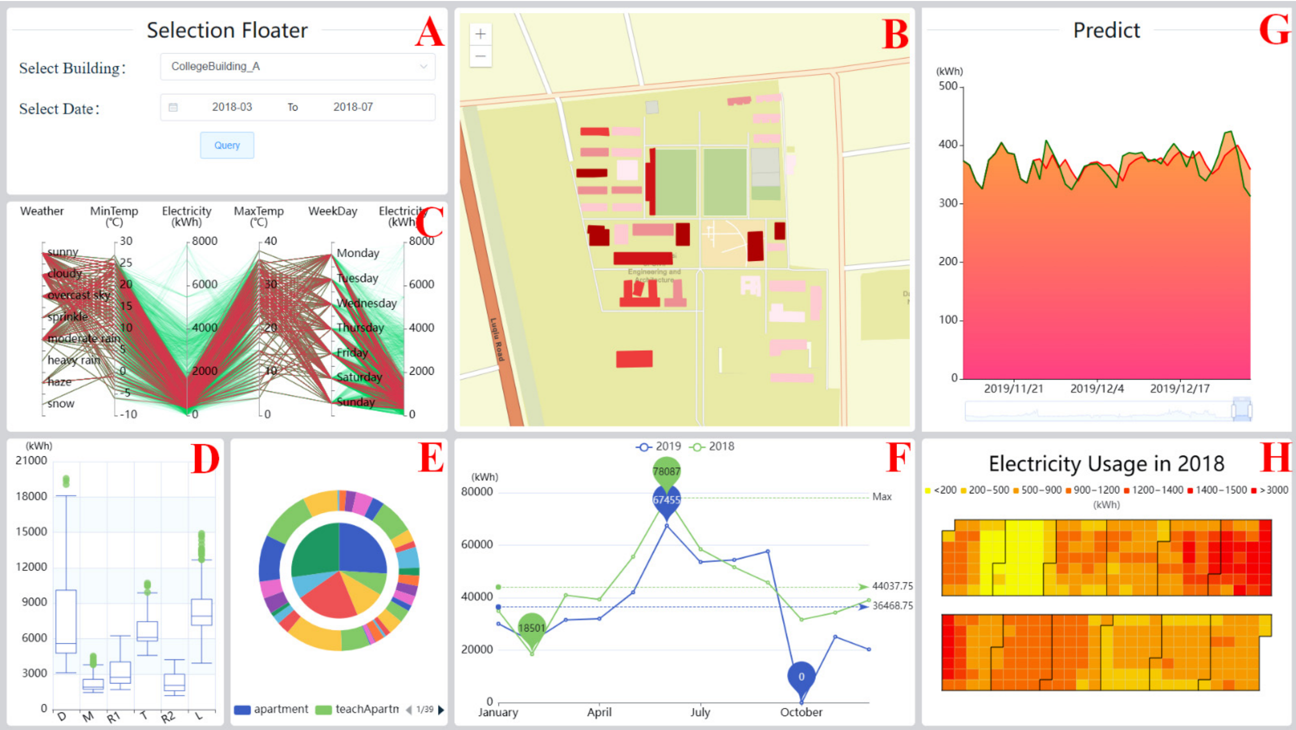


Figure 7. The SmartEle system. (**A**) denotes the selection panel. (**B**) denotes the heat map view. (**C**) denotes the electricity consumption related factors view. (**D**) denotes the anomaly monitoring view. (**E**) denotes the electricity consumption percentage view. (**F**) denotes the electricity consumption trend view. (**G**) denotes the electricity consumption predict view. (**H**) denotes the electricity consumption calendar view. In (**C**), D denotes the dormitory community, M denotes the master and doctoral apartment community, R1 denotes the research community, T denotes the teaching community, R2 denotes the recreation community and L denotes the logistics community.

5.2. Analysis of Electricity Consumption Behavior

5.2.1. Analysis of the Variation in Electricity Consumption by User Groups

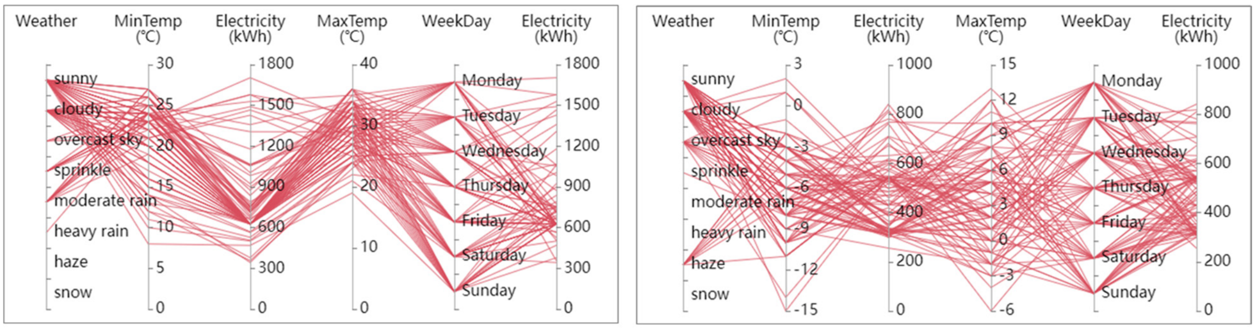
First, it is necessary to understand the heterogeneity of the users and then analyze the differences in electricity consumption of these user groups by exploring the power consumption patterns of different regions. Figure 7B,E shows the difference in electricity consumption for different functional communities. Figure 7B shows the difference in electricity consumption between buildings in the form of a heat map, with darker colors indicating higher electricity consumption. Figure 7E shows the difference in electricity consumption by calculating the proportion of electricity consumption for each building. By combining the distribution of electricity consumption in Figure 7B,E, one can see differences in the electricity consumption of buildings with different functional attributes in the campus. Among these, the most electricity is consumed by the logistics community, accounting for 27.2% of the entire campus consumption. The largest electricity consumers in this functional region are the cafeteria and the boiler room, which allow students and the faculty to carry out their studies and lives. The dormitory community is the second largest functional region in terms of electricity consumption, accounting for 26.02% of the entire campus. Within the community, Dormitory No. 5 has the highest electricity consumption because it has the most floors: nine aboveground floors and one underground floor. The next is Dormitory No. 9, which has nine aboveground floors. The rest of the dormitory buildings are all structures with six aboveground stories, and their electricity consumption does not differ significantly. The teaching community is the third largest functional region in terms of electricity consumption, accounting for 21.55% of the entire campus. In this community, Block B consumes significantly more electricity than other buildings in the district because it contains services with high electricity consumption such as machine rooms, the campus network information center and printing rooms. The electricity consumption of the research community, recreation community and master and doctoral apartment community does not vary much, accounting for 10.36%, 7.5% and 7.37% respectively. The percentage of electricity consumed by each building in the research community is between 1% and 3%, and the variability of electricity consumption is not significant. Within the recreation community, the gymnasium complex uses the most electricity because the venue has the most entertainment facilities compared with the others. In contrast, the electricity consumption of the master and doctoral apartment community is stable and concentrated, which may be related to the fact that the community is a place where teachers and their families live, and their work and rest are regular and less affected by holidays.

5.2.2. Anomaly Monitoring

There will be abnormal electricity consumption during system operation. Boxplots were used to monitor abnormal data and display the distribution status of the data at the same time. The six boxes in Figure 7D represent six types of functional community (left to right: dormitory community, master and doctoral apartment community, research community, teaching community, recreation community and logistics community). It can be seen in Figure 7D that the logistic community has a high abnormal value, indicating that there is more abnormal high-intensity electricity consumption in this functional community. However, the median electricity consumption of the dormitory community deviates from the center of the upper and lower quartiles, showing a strong distribution skewness, indicating that there is greater volatility in the electricity consumption of this community.

5.2.3. Correlation Analysis of Electricity Consumption Factors

Campus electricity consumption is affected by weather and special dates; therefore, focus context technology was used to explore the correlations of building electricity consumption factors in a specific period. Taking Building F of the college as an example, the correlations between electricity consumption and both weather and day of the week was established. The results are shown in Figure 8. The red line in Figure 8a is the electricity consumption from July to September 2018, and the red line in Figure 8b is the electricity consumption from December 2018 to February 2019. It can be roughly seen from Figure 8a that when the temperature is between 30 and 40 °C, the electricity consumption increases correspondingly as the temperature rises. The power consumption range is 600–1500 kWh on working days and 300–900 kWh on weekends. In Figure 8b, the electricity consumption shows an increasing trend as the temperature decreases. It can also be seen that the electricity consumption range is 300–500 kWh on working days and 300–800 kWh on weekends. On balance, winter electricity consumption is lower than summer electricity consumption. This may be related to the higher use of air conditioning in summer but not using electricity as the main heat source in winter. Weekend electricity consumption is slightly lower than that on weekdays, which is consistent with the normal work and rest time of students.



(a) (b)

Figure 8. Analysis of factors influencing electricity consumption. (**a**) Electric consumption of July–September 2018. (**b**) Electric consumption of December–February 2019.

5.3. Awareness of the Electricity Consumption Situation

Multi-granularity sensing of electricity consumption situation awareness is needed to capture the evolution of electricity consumption patterns over time and to sense campus electricity consumption at coarse- and fine-grained levels. The electricity consumption data are counted in days and months, and the trend line of electricity consumption over time is plotted. For example, Figure 7F shows the monthly electricity consumption statistics. Figure 7H shows the daily electricity consumption statistics. The graphs show that there is a difference in the pattern of electricity consumption in different periods, which, in general, is divided into peak, plateau and valley periods.

The overall campus electricity consumption data are shown in Figure 7F, with the green line representing electricity consumption in 2018 and the blue line representing electricity consumption in 2019. As indicated by the folding line, the two ends are low, and the middle is high. The electricity consumption between July and September shows a peak pattern, February shows a valley pattern, and the other months have little difference in electricity consumption, indicating a stable period. This phenomenon echoes the colors of the same interval in Figure 7H. This trend is mainly due to the fact that July to September is in the summer season when the use of air conditioners increases significantly. In winter, on the other hand, the frequency of air conditioning use is low because of the heating facilities. On the other hand, the Chinese New Year is in February, and this period is a holiday, so electricity consumption is significantly reduced. Overall, electricity consumption in 2019 was slightly lower than in 2018. In October 2019, the signal was interrupted due to system maintenance, resulting in missing data for October, which is also reflected in the anomaly monitoring view. In addition, a relationship between electricity consumption and weekdays was identified. In Figure 8, the research community and teaching community used more electricity on weekdays than on non-workdays.

5.4. Electricity Demand Prediction

The prediction accuracy of the existing models is limited due to the poor regularity of the historical data. This present study was based on the ATT-LSTM model, which considers the synergy of a set of time series with similar characteristics to predict future short-term electricity demand. Using the dormitory community as an example, first, the daily electricity consumption of buildings was counted for a total of 730 days from 2018 to 2019, and operations such as data pre-processing, filling in missing values and normalization were performed. After the correlation analysis, the similarity metric matrix was generated, as shown in Figure 9. The values in the matrix indicate the correlation between two buildings. Time series with a correlation greater than 85% were selected to synergistically enhance the data to compensate for the shortcomings caused by the non-smoothness of single-series data. Finally, a set of time series with similar characteristics was inputted into the ATT-LSTM model, and 694 days of data were used as the training set, and 36 days of data as the test set, with 6 days of historical electricity consumption data being used to train 1 day of electricity consumption data. As shown in Figure 7G, the red line indicates the predicted electricity from 25 November to 31 December 2019 for Building No. 1 in the student dormitory community. The green line indicates the actual electricity consumption of the building.

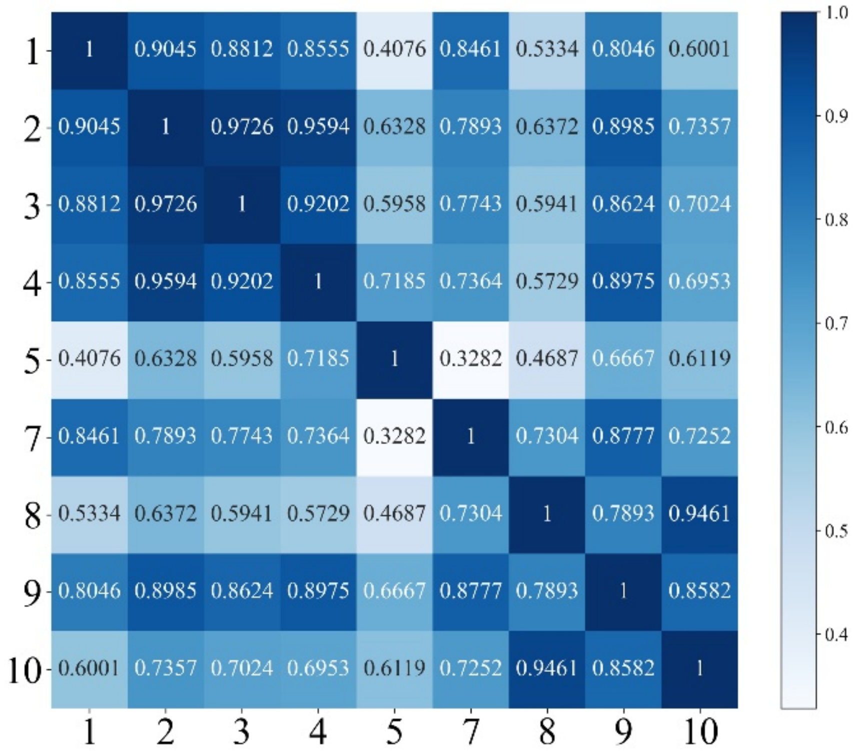


Figure 9. Similarity metric matrix. The horizontal and numerical axes indicate the i-th dormitory building.

6. Discussion

6.1. Usability of Interactive Visualization for Discovering Spatiotemporal Patterns

In the SmartEle system, a series of analysis methods has been designed for different requirements. The feasibility of these methods to support the analysis was evaluated by verifying whether they addressed campus electricity issues and challenges better than traditional analysis methods. Their usefulness was evaluated in terms of the following aspects: comprehensive electricity consumption data perception, short-term building electricity demand prediction, effective visualization of multidimensional data and system universality.

Integrated electricity consumption data perception was achieved by designing a novel glyph symbol, as shown in Figure 10a. The glyphs consist of the identified important data features that represent the electricity consumption patterns of different groups, i.e., the daily and monthly electricity consumption of specific functional community and the electricity consumption of individual buildings within a specific functional community. Figure 10b shows a separate visualization for each of the three types of data. In general, traditional visualization presents a single piece of data in a certain way, or presents the results of data analysis. Although this can also reflect data information to some extent, it is difficult to dig deeper into the data. The visualization method proposed is better able to display more information in a limited visual space and is more conducive to comparative analysis of electricity consumption between groups (functional communities) and within groups (buildings), solving the challenge of effectively obtaining important data features from complex data.

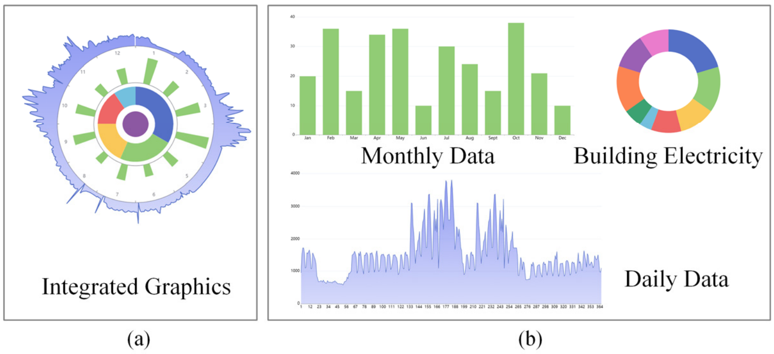


Figure 10. (**a**) Integrated visualization and (**b**) traditional visualization of electricity consumption data.

Prediction of the short-term electricity demand by a building was based on a hybrid ATT-LSTM model that considers the synergy of similar time series. This study established a comparison experiment for LSTM model predictions. Here, short-term electricity demand forecasts were made using Dormitory No. 1 as an example. The two models were run separately for 2000 rounds and the models were evaluated by MAE, RMSE and MAPE metrics. The operational results showed that the average running time of the ATT-LSTM model proposed was 0.24 s per 100 rounds, while the LSTM model took 0.46 s. Figure 11 shows the predicted values of the ATT-LSTM model and LSTM model compared with the true values. A comparison of the models is shown in Table 1. In the model evaluation results, the proposed method reduced the MAE by 59%, the RMSE by 66% and the MAPE by 26%, compared with the LSTM model. MAE and RMSE are related to the magnitude of the true value, so the accuracy is measured by the MAPE. In a number of existing studies, a MAPE range of 0.0215–0.058 indicated adequate predictions, so the prediction accuracy of the model proposed is within the acceptable error range. This means that the method proposed can accurately predict electricity demand.

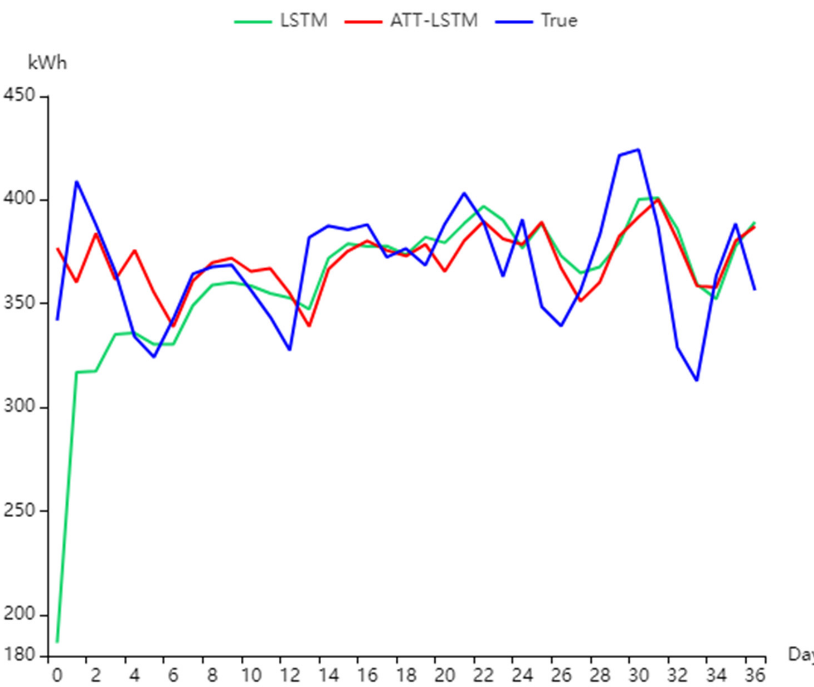


Figure 11. Comparison of predicted values of the ATT-LSTM prediction model, the LSTM prediction model and the true values.

Table 1. Model comparison.

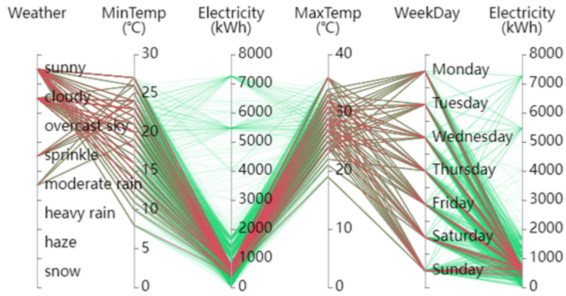
Model	MAE	RMSE	MAPE
LSTM	0.0103	0.0157	0.0346
ATT-LSTM	0.0042	0.0053	0.0256
ANFIS [49]		0.067	0.027892
WT-Adam-LSTM [50]	0.81	1.14	0.0215
Hybrid model [51]	2.07	3.28	0.0277
Hybrid model [52]		1.99	0.034
ELM-GA [53]	4.39		0.058

A parallel coordinate system can visually describe the correlations of multidimensional data. Figure 12a,b shows parallel coordinate systems describing multidimensional data correlations using a focus context, and Figure 12c is a normal parallel coordinate system. Overall, the approach proposed to the visualization of the data of interest reflects more detail than a normal coordinate system. For example, the red line in Figure 12a marks the electricity consumption of Building A from August to September 2018. The green line shows the electricity consumption data of other buildings in the same time interval. In this view, one can see how the building of interest is distributed within the overall electricity consumption for a specific time period, and observe the correlation between electricity consumption and related factors. Based on this, the data of interest can be further focused on to view the specific electricity consumption and discover more detailed information, as shown in Figure 12b. However, in Figure 12c, this information is masked.

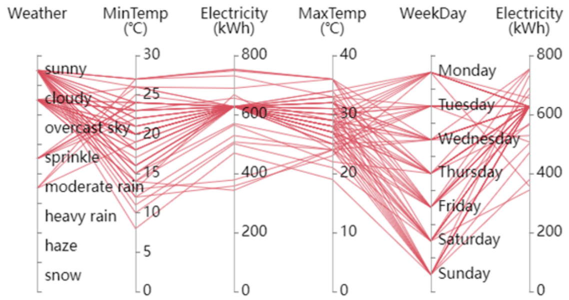
Although the proposed system has been developed for the electricity consumption data of a particular campus, it can be easily applied to other similar scenarios, such as visualizing the electricity consumption data of another campus or community. In such similar problems, the visualization-driven model can be adjusted by the data features of specific scenarios to show the electricity consumption data of other power systems, so the SmartEle system has some universality. In addition, the proposed system is scalable to combine many types of data, such as grid distribution and equipment information.

6.2. Experience Analysis of Electricity Consumption Patterns within the Campus

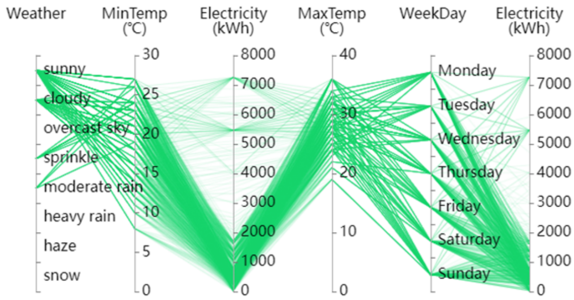
In order to explore the overall electricity consumption characteristics of the campus and to extract the electricity demand of different groups and the differences in electricity consumption among groups, a comparative analysis of the electricity consumption data of different groups was conducted and the results are shown in Figure 13. The folded area chart in the figure represents the daily electricity consumption for a total of 365 days in 2019. The bar chart represents the monthly electricity consumption for a total of 12 months in 2019, with larger areas indicating higher electricity consumption in that month. The pie chart indicates the electricity consumption of the individual buildings in the designated functional community, and the size of the segment indicates the electricity consumption (the electricity consumption was recorded as zero in October due to system debugging). As can be seen in Figure 13, for different groups, there are significant imbalances in electricity consumption, fluctuations in electricity consumption and the proportion of electricity consumption in buildings within a functional community.



(a) Parallel coordinate systems using focus contexts



(b) A more focused parallel coordinate systems using focus contexts



(c) Ordinary parallel coordinate system

Figure 12. Correlation analysis of multidimensional data.

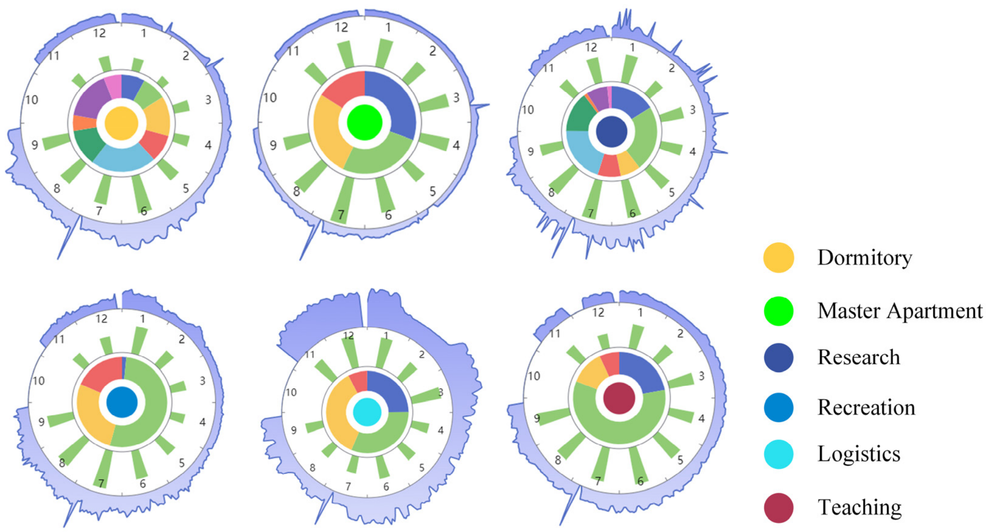


Figure 13. Differences in electricity consumption among user groups.

In terms of electricity consumption, there are differences in the electricity demand of different groups (functional communities). The electricity consumption of the logistics community is in the range from 7000 to 15,000 kWh, which is significantly higher than that of other functional communities; this is the community at the (first) highest level of demand. Next are the research community, teaching community and dormitory community, for which the electricity consumption ranges from 4000 to 10,000 kWh, which is the second level of demand. Next comes the recreation community, which uses 3000 to 9000 kWh of electricity and belongs to the third level of demand. Finally, the electricity consumption of the master and doctoral apartment community is in the range from 1500 to 2000 kWh, creating the fourth level of demand.

In terms of electricity consumption fluctuations, different groups (functional communities) have their own patterns of electricity consumption behavior. Among them, the electricity consumption in the research community fluctuates greatly, and the graph also shows multiple peaks in this functional community, which may be related to the scientific research tasks carried out by this functional community. The folded area chart of the logistic community is higher in the upper half of the circle (the first half of January to the second half of March, and November to December) than the lower half of the circle (April to September), which is related to the fact that the upper half of the circle belongs to the winter season and the heating needs of the logistic community are great. The shape is jagged, indicating a certain fluctuation in electricity consumption in this functional community. In contrast to the logistic community, for the dormitory community, the lower half of the folded area chart (April to September) is higher than the upper half of the graph (January to March and November to December), which is due to the fact that the summer season is in the lower half of the graph, and the demand for air conditioner use is high during that period, causing an increase in electricity consumption. The second half of January to the first half of February is in the winter holiday period, so electricity consumption tends to reduce. The recreational community has high electricity consumption in winter and summer, with school holidays occurring from the second half of January to the first half of February, and in August. Some of the recreational community, however, is usually open to the public during that period, so there is still high demand for electricity during this period. The electricity consumption of the master and doctoral apartment community and the teaching community is relatively stable, mainly because the master and doctoral apartment community is a place where teachers live and is less affected by weekdays and holidays. The teaching community is where the task of teaching is carried out and is used in accordance with the school's academic planning, so electricity consumption is less subject to other factors.

In terms of the share of electricity consumption in individual buildings, there are differences in the share of electricity consumption within different functional communities. The most balanced distribution of electricity consumption was found in the master and doctoral apartment community. There are large differences in electricity consumption among the buildings within the research community, with the lowest electricity consumption being in the rainwater lab and the underground engineering lab, and this difference is mainly related to the research tasks. In the dormitory community, except for Building No. 5, which has a relatively large share of electricity consumption, the electricity consumption is not very different. Academic Building B has several computer rooms, so this building has the largest share of electricity consumption. In the recreation community, the distribution of electricity consumption is obviously different due to the difference in the scale of the place itself and the services provided. In the logistics community, the electricity consumption of the integrated office building is less than that of other buildings, and the difference in electricity consumption of other buildings is smaller.

7. Conclusions

In this study, a variety of data mining techniques, including a visualization method to analyze and predict campus electricity consumption, were designed and developed to provide a multi-view linked collaborative interactive visualization system, called SmartEle. A case study was carried out for the campus of the studied university. This study focused on group heterogeneity and a group-oriented analysis of user electricity consumption patterns. Usually, users are unable to focus on multiple data at the same time. To address this challenge, a visualization-driven data mining model that integrates multiple data features into a single graph was proposed. This visualization supports the detection of campus electricity consumption at multiple granularities, which can effectively solve the challenge of reducing the cognitive burden of system users. The prediction accuracy of existing models for weakly regular data is limited. In this study, a multivariate synergistic prediction model was proposed by considering the synergistic effects of similar electricity consumption time series. Compared with the LSTM model, the model proposed reduced the MAE by 59%, the RMSE by 66% and the MAPE by 26%. On average, it was faster by 0.22 s per 100 rounds of training on average. This shows that this study improved the prediction accuracy and reduced the running time.

There is room for improvement in this work. More granular analysis by floors or rooms will be our future work.

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References

1. Reddy, B.S. Access to modern energy services: An economic and policy framework. *Renew. Sustain. Energy Rev.* **2015**, *47*, 198–212. [CrossRef]
2. Olatomiwa, L.; Blanchard, R.; Mekhilef, S.; Akinyele, D. Hybrid renewable energy supply for rural healthcare facilities: An approach to quality healthcare delivery. *Sustain. Energy Technol. Assess.* **2018**, *30*, 121–138. [CrossRef]
3. Mehmood, U. Contribution of renewable energy towards environmental quality: The role of education to achieve sustainable development goals in G11 countries. *Renew. Energy* **2021**, *178*, 600–607. [CrossRef]
4. Rădulescu, C.; Toader, R.; Boca, G.; Abrudan, M.; Anghel, C.; Toader, D.C. Sustainable Development in Maramures County. *Sustainability* **2015**, *7*, 7622–7643. [CrossRef]
5. Cazenave, M.; Pachauri, S. A model of energy poverty and access: Estimating household electricity demand and appliance ownership. *Energy Econ.* **2021**, *98*, 105266. [CrossRef]
6. Van Ruijven, B.J.; De Cian, E.; Sue Wing, L. Amplification of future energy demand growth due to climate change. *Nat. Commun.* **2019**, *10*, 2762. [CrossRef]
7. Shahbaz, M.; Topcu, B.A.; Sarıgül, S.S.; Vo, X.V. The effect of financial development on renewable energy demand: The case of developing countries. *Renew. Energy* **2021**, *178*, 1370–1380. [CrossRef]
8. Swan, L.G.; Ugursal, V.I. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renew. Sustain. Energy Rev.* **2009**, *13*, 1819–1835. [CrossRef]
9. Iqbal, M.N.; Kütt, L. End-user electricity consumption modelling for power quality analysis in residential building. In Proceedings of the 2018 19th International Scientific Conference on Electric Power Engineering (EPE), Brno, Czech Republic, 16–18 May 2018; pp. 1–6.
10. Iqbal, M.N.; Kütt, L.; Rosin, A. Complexities associated with modeling of residential electricity consumption. In Proceedings of the 2018 IEEE 59th International Scientific Conference on Power and Electrical Engineering of Riga Technical University (RTUCON), Riga, Latvia, 12–13 November 2018.

11. Gu, J. *Research on On Circulation Structure and Space Organiation of University Campus*; Inner Mongolia Agricultural University: Hohhot, China, 2015.
12. Liu, J.; Yang, T.; Fan, P. Research on Influencing Factors of Provincial Cities'Urban Residential Power Consumption under the Spatial Effect. *Build. Sci.* **2020**, *36*, 312–318.
13. Guo, F. *Study on the Chinese Rural Household Conmmercial Energy Consumption and Its Influence Factors*; China University of Mining and Technology: Xuzhou, China, 2015.
14. Ramnath, G.S.; Harikrishnan, R. Households Electricity Consumption Analysis: A Bibliometric Approach. *Libr. Philos. Pract.* **2021**, *5098*, 1–21.
15. Santiago, I.; Lopez-Rodriguez, M.A.; Trillo-Montero, D.; Torriti, J.; Moreno-Munoz, A. Activities related with electricity consumption in the Spanish residential sector: Variations between days of the week, Autonomous Communities and size of towns. *Energy Build.* **2014**, *79*, 84–97. [CrossRef]
16. Wang, Y.; Chen, Q.; Kang, C. Electricity Consumer Behavior Model. In *Smart Meter Data Analytics*; Springer: Singapore, 2020; pp. 37–57. [CrossRef]
17. Avordeh, T.K.; Gyamfi, S.; Opoku, A.A. Estimating Residential Electricity Consumption for Appliance Use: A Statistical Model Approach. In Proceedings of the 2021 International Conference on Electrical, Computer and Energy Technologies (ICECET), Cape Town, South Africa, 9–10 December 2021; pp. 1–10.
18. Wang, Y.; Bennani, I.L.; Liu, X.; Sun, M.; Zhou, Y. Electricity Consumer Characteristics Identification: A Federated Learning Approach. In Proceedings of the IEEE Transactions on Smart Grid, Cape Town, South Africa, 9–10 December 2021; pp. 3637–3647.
19. Jing, C.F.; Du, M.Y.; Li, S.N.; Liu, S.Y. Geospatial Dashboards for Monitoring Smart City Performance. *Sustainability* **2019**, *11*, 5648. [CrossRef]
20. Gegner, K.M.; Overbye, T.G.; Shetye, K.S.; Weber, J.D. Visualization of power system wide-area, time varying information. In Proceedings of the Institute of Electrical and Electronics Engineers Inc, Urbana, IL, USA, 19–20 February 2016.
21. Xiao, Y.; Fei, Z.; Zheng, K.; Zheng, T.; Qian, B.; Zheng, W. A Survey of Power Grid Operation State Visualization. *J. Comput.-Aided Des. Comput. Graph.* **2019**, *31*, 1750–1758.
22. Fang, J.; Peng, X.; Liu, T.; Chen, Y.; Li, W.; Wen, J.; Xiong, L.; Wang, H. Development trend and application prospects of big data-based condition monitoring of power apparatus. *Power Syst. Prot. Control* **2020**, *13*, 176–186.
23. Zhang, S.; Liu, J.; Zhao, B.; Cao, J. Cloud Computing-Based Analysis on Residential Electricity Consumption Behavior. *Power Syst. Technol.* **2013**, *37*, 1542–1546.
24. Xu, L.; Yang, X.; Zhang, M. Industrial users of electricity behavior analysis based on data mining. *Electr. Meas. Instrum.* **2017**, *54*, 68–74.
25. Xu, J.; Kang, X.; Chen, Z.; Yan, D.; Guo, S.; Jin, Y.; Hao, T.; Jia, R. Clustering-based probability distribution model for monthly residential building electricity consumption analysis. *Build. Simul.* **2021**, *14*, 1–16. [CrossRef]
26. Rathod, R.R.; Garg, R.D. Regional electricity consumption analysis for consumers using data mining techniques and consumer meter reading data. *Int. J. Electr. Power Energy Syst.* **2016**, *78*, 368–374. [CrossRef]
27. Lu, J.; Zhu, Y.; Wenhao, P.; Sun, Y. Feature Selection Strategy for Electricity Consumption Behavior Analysis in Smart Grid. *Autom. Electr. Power Syst.* **2017**, *41*, 58–63. (In Chinese)
28. Gong, G.; Chen, Z.; Lu, J.; Wang, C.; Qi, B.; Cui, G. Clustering Optimization Strategy for Electricity Consumption Behavior Analysis in Smart Grid. *Autom. Electr. Power Syst.* **2018**, *42*, 58–63.
29. Wang, C.; Zheng, H. A portrait of electricity consumption behavior mode of power users based on fuzzy clustering. *Electr. Meas. Instrum.* **2018**, *55*, 77–81.
30. Zhang, L.; Xu, C.; Wang, L.; Li, C. User profile model of park based on multi-dimensional energy consumption analysis. *Renew. Energy Resour.* **2021**, *39*, 1078–1086.
31. Guo, C.; Hong, F.; Chen, J.; Li, Y.; Xu, Y.; Xi, J.; Wang, J. Application of Scientific Visualization to Power Systems. *Water Resour. Power* **2011**, *29*, 146–149.
32. Netek, R.; Brus, J.; Tomecka, O. Performance Testing on Marker Clustering and Heatmap Visualization Techniques: A Comparative Study on JavaScript Mapping Libraries. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 348. [CrossRef]
33. Zhao, L.; Wang, L.; Liu, Y.; Sun, P.; Zhang, L. Research and Analysis on Visualization Technology for Power Grid Real-Time Monitoring. *Power Syst. Technol.* **2014**, *38*, 538–543.
34. Hou, X.; Xiao, D.; Chen, P.; Song, L. Visual analysis system for electrical behavior data. *J. Comput. Appl.* **2018**, *38*, 77–82.
35. Zhao, Z.; Zhang, T.; Huang, Y.; Zheng, W.; Wei, C. Simulation-based visual analysis of power grid operation mode. *J. Zhejiang Univ.* **2020**, *47*, 36–44.
36. Fang, S.; Wang, L.; Gao, M.; Qian, R.; Chen, X.; Shen, L.; Zhang, L.; Liu, R.; Wang, Q. Interactive Power Data Visualization and Analysis. *J. Nanjing Norm. Univ.* **2019**, *42*, 96–106.
37. Li, W.; Cheng, X.; Lu, Q. A Graph-Based Method for Visual Analysis of Power Data. *J. Graph.* **2019**, *40*, 124–130.
38. Lu, Q.; Xu, W.; Zhang, H.; Tang, Q.; Li, J.; Fang, R. ElectricVIS: Visual analysis system for power supply data of smart city. *J. Supercomput.* **2020**, *76*, 793–813. [CrossRef]
39. Hippert, H.S.; Pedreira, C.E.; Souza, R.C. Neural networks for short-term load forecasting: A review and evaluation. *IEEE Trans. Power Syst.* **2001**, *16*, 44–55. [CrossRef]

40. Kwon, B.S.; Park, R.J.; Song, K.B. Short-Term Load Forecasting Based on Deep Neural Networks Using LSTM Layer. *J. Electr. Eng. Technol.* **2020**, *15*, 1501–1509. [CrossRef]
41. Guan, T.; Xu, Z.; Lin, L.; Zhang, G.; Jia, Y.; Shi, Y. Maximum Incremental Load Recursive Model Based on LS-SVM Considering Accumulated Temperature Effect. In Proceedings of the 2018 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), Halifax, NS, Canada, 30 July–3 August 2018; pp. 716–719.
42. Yang, D.; Yang, J.; Hu, C.; Cui, D.; Chen, Z. Short-term power load forecasting based on improved LSSVM. *Electron. Meas. Technol.* **2021**, *44*, 47–53.
43. Tang, X.L.; Dai, Y.Y.; Liu, Q.; Dang, X.Y.; Xu, J. Application of Bidirectional Recurrent Neural Network Combined with Deep Belief Network in Short-Term Load Forecasting. *IEEE Access* **2019**, *7*, 160660–160670. [CrossRef]
44. Petroșanu, D.-M. Designing, Developing and Validating a Forecasting Method for the Month Ahead Hourly Electricity Consumption in the Case of Medium Industrial Consumers. *Processes* **2019**, *7*, 310. [CrossRef]
45. Zheng, J.; Xu, C.; Zhang, Z.; Li, X. Electric load forecasting in smart grids using Long-Short-Term-Memory based Recurrent Neural Network. In Proceedings of the 2017 51st Annual Conference on Information Sciences and Systems (CISS), Baltimore, MD, USA, 22–24 March 2017; pp. 1–6.
46. Dudek, D.; Pełka, P.; Smyl, S. A Hybrid Residual Dilated LSTM and Exponential Smoothing Model for Midterm Electric Load Forecasting. *IEEE Trans. Neural Netw. Learn. Syst.* **2020**, 1–13. [CrossRef]
47. Deng, D.; Li, J.; Zhang, Z.; Teng, Y.; Huang, Q. Short-term Electric Load Forecasting Based on EEMD-GRU-MLR. *Power Syst. Technol.* **2020**, *44*, 593–602.
48. Lu, H.; Ma, X.; Ma, M. A hybrid multi-objective optimizer-based model for daily electricity demand prediction considering COVID-19. *Energy* **2021**, *219*, 119568. [CrossRef] [PubMed]
49. Pourdaryaei, A.; Mokhlis, H.; Illias, H.A.; Kaboli, S.H.A.; Ahmad, S. Short-Term Electricity Price Forecasting via Hybrid Backtracking Search Algorithm and ANFIS Approach. *IEEE Access* **2019**, *7*, 77674–77691. [CrossRef]
50. Chang, Z.; Zhang, Y.; Chen, W. Electricity price prediction based on hybrid model of adam optimized LSTM neural network and wavelet transform. *Energy* **2019**, *187*, 115804. [CrossRef]
51. Zhang, J.; Tan, Z.; Wei, Y. An adaptive hybrid model for short term electricity price forecasting. *Appl. Energy* **2020**, *258*, 114087. [CrossRef]
52. Zhang, J.; Zhang, Y.; Li, D.; Tan, Z.; Ji, J. Forecasting day-ahead electricity prices using a new integrated model. *Int. J. Electr. Power Energy Syst.* **2019**, *105*, 541–548. [CrossRef]
53. Ahmad, W.; Ayub, N.; Ali, T.; Irfan, M.; Awais, M.; Shiraz, M.; Glowacz, A. Towards Short Term Electricity Load Forecasting Using Improved Support Vector Machine and Extreme Learning Machine. *Energies* **2020**, *13*, 2907. [CrossRef]